Supplementary Information

Tree height and leaf drought tolerance traits shape growth responses across droughts in a temperate broadleaf forest

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List of Tables

1	Table 51. Monthly Palmer Drought Severity Index (PDSI), and its rank among all years	
	between 1950 and 2009 (driest=1), for focal droughts	2
2	Table S2. Species-specific bark thickness regression equations	:
3	Table S3. Species-specific height regression equations	4
4	Table S4. Individual tests of species traits as drivers of drought resistance, where Rt is used as	
	the response variable.	
5	Table S5. Individual tests of species traits as drivers of drought resistance, where Rt_{ARIMA} is	
	used as the response variable	6
6	Table S6. Summary of top full models for each drought instance, where Rt is used as the	
	response variable	7
7	Table S7. Summary of top models for each drought instance, where Rt_{ARIMA} is used as the	
	response variable	8
List	of Figures	
1	Figure S1. Time series of Palmer Drought Severity Index (PDSI) for the 2.5 years	
	right S1. Time series of raimer Brought Severity Index (1 BS1) for the 2.0 years	
	prior to each focal drought	ç
2		ę
2	prior to each focal drought	10
2	prior to each focal drought	
	prior to each focal drought	10
3	prior to each focal drought	10
3	prior to each focal drought Figure S2. Map of ForestGEO plot showing topographic wetness index and location of cored trees. Scale units are in meters Figure S3. Distribution of reconstructed tree heights across drought years. Figure S4. Distribution of independent variables by species. Species that are assigned	10
3 4	prior to each focal drought Figure S2. Map of ForestGEO plot showing topographic wetness index and location of cored trees. Scale units are in meters Figure S3. Distribution of reconstructed tree heights across drought years. Figure S4. Distribution of independent variables by species. Species that are assigned the same letter are not significantly different from each other with regard to the tested variable.	10
3 4	prior to each focal drought Figure S2. Map of ForestGEO plot showing topographic wetness index and location of cored trees. Scale units are in meters Figure S3. Distribution of reconstructed tree heights across drought years. Figure S4. Distribution of independent variables by species. Species that are assigned the same letter are not significantly different from each other with regard to the tested variable. Figure S5. Comparison of Rt and Rt _{ARIMA} results, with residuals, for each drought	10 11 12

Table S1. Monthly Palmer Drought Severity Index (PDSI), and its rank among all years between 1950 and 2009 (driest=1), for focal droughts.

year	month	PDSI	rank
1966	May	-2.98	2
	June	-3.40	2
	July	-4.08	2
	August	-4.82	1
1977	May	-2.96	3
	June	-3.28	3
	July	-3.61	3
	August	-3.68	3
1999	May	-3.63	1
	June	-4.21	1
	July	-4.53	1
	August	-4.64	2

Table S2. Species-specific bark thickness regression equations $\,$

Species	Equations	R^2
Carya cordiformis	$\ln[B] = -1.56 + 0.416 \ln[DBH]$	0.226
Carya glabra	ln[B] = -0.393 + 0.268*ln[DBH]	0.040
Carya ovalis	ln[B] = -2.18 + 0.651*ln[DBH]	0.389
Carya tomentosa	$\ln[B] = -0.477 + 0.301 \cdot \ln[DBH]$	0.297
Fagus grandifolia	$\ln[B] = 1 * \ln[DBH]$	
Fraxinus americana	ln[B] = 0.418 + 0.268*ln[DBH]	0.256
Juglans nigra	ln[B] = 0.346 + 0.279*ln[DBH]	0.246
Liriodendron tulipifera	ln[B] = -1.14 + 0.463*ln[DBH]	0.545
Quercus alba	$\ln[B] = -2.09 + 0.637 \ln[DBH]$	0.603
Quercus prinus	$\ln[B] = -1.31 + 0.528 \ln[DBH]$	0.577
Quercus rubra	ln[B] = -0.593 + 0.292*ln[DBH]	0.087

Table S3. Species-specific height regression equations

Species	Equations	R^2
Carya cordiformis	ln[H] = 0.332 + 0.808*ln[DBH]	0.874
Carya glabra	ln[H] = 0.685 + 0.691*ln[DBH]	0.841
Carya ovalis	$\ln[H] = 0.533 + 0.741 \ln[DBH]$	0.924
Carya tomentosa	$\ln[H] = 0.726 + 0.713 \ln[DBH]$	0.897
Fagus grandifolia	$\ln[H] = 0.708 + 0.662 * \ln[DBH]$	0.857
Liriodendron tulipifera	ln[H] = 1.33 + 0.52*ln[DBH]	0.771
Quercus alba	ln[H] = 0.74 + 0.645*ln[DBH]	0.719
Quercus prinus	ln[H] = 0.41 + 0.757*ln[DBH]	0.886
Quercus rubra	$\ln[H] = 1.00 + 0.574 \ln[DBH]$	0.755
all	ln[H] = 0.839 + 0.642*ln[DBH]	0.857

Table S4. Individual tests of species traits as drivers of drought resistance, where Rt is used as the response variable.

		all droughts		1966		1977		1999	
variable	category	$\Delta { m AICc}$	coefficients						
xylem porosity	R	-0.80	0.0630	2.29**	0.190	1.92*	-0.152	3.36**	0.1500
	D/SR		0.0000		0.000		0.000		0.0000
PLA	•	6.70	-0.0140	9.13**	-0.025	-0.32	-0.010	-0.95	-0.0070
LMA		-2.01	0.0002	-1.9	0.001	-1.68	-0.002	-2.03	0.0003
π_{tlp}		1.33	-0.1740	-1.65	-0.107	1.23*	-0.245	-0.1	-0.1690
WD		-1.97	-0.0310	-1.26	-0.206	-1.44	-0.154	0.66	0.2720

Variable abbreviations are as in Table 2. $\Delta AICc$ is the AICc of a model excluding the trait minus that of the model including it.

^{*} $\Delta {\rm AICc} > 1$: variable meets $\Delta {\rm AICc}$ criterion for inclusion in full model

^{**} $\Delta AICc > 2$: variable is considered significant as an individual predictor (and meets $\Delta AICc$ criterion for inclusion in full model)

Table S5. Individual tests of species traits as drivers of drought resistance, where Rt_{ARIMA} is used as the response variable.

		all droughts		1966		1977		1999	
variable	category	$\Delta { m AICc}$	coefficients						
xylem porosity	R	-1.47	0.0420	0.95	0.1520	2.84**	-0.171	2.27**	0.155
	D/SR		0.0000		0.0000		0.000		0.000
PLA	•	4.48**	-0.0120	10.15**	-0.0240	-0.9	-0.008	-1.67	-0.005
LMA		-1.99	-0.0003	-2.02	0.0005	-0.42	-0.003	-1.9	0.001
π_{tlp}		0.42	-0.1510	-1.94	-0.0530	-0.53	-0.179	0.04	-0.200
WD		-1.94	-0.0390	-0.08	-0.3040	-1.57	-0.142	0.83	0.316

Variable abbreviations are as in Table 2. $\Delta AICc$ is the AICc of a model excluding the trait minus that of the model including it.

^{*} $\Delta AICc > 1$: variable meets $\Delta AICc$ criterion for inclusion in full model

^{**} $\Delta {\rm AICc} > 2$: variable considered significant as an individual predictor

Table S6. Summary of top full models for each drought instance, where Rt is used as the response variable.

drought	$\Delta { m AICc}$	R^2	Intercept	ln[H]	ln[TWI]	ln[H]*ln[TWI]	PLA	π_{tlp}
all	0.000	0.12	1.131	-0.057	-0.086	-	-0.012	-0.113
	0.583	0.11	1.423	-0.055	-0.086	-	-0.013	-
	0.726	0.12	1.537	-0.202	-0.326	0.082	-0.012	-0.114
	1.352	0.11	1.826	-0.198	-0.324	0.081	-0.013	-
1966	0.000	0.25	1.622	-0.135	-	-	-0.025	-
1977	0.000	0.22	0.503	-	-0.144	-	-	-0.24
	0.908	0.21	1.069	-	-0.144	-	-	-
	0.988	0.22	0.568	-0.03	-0.139	-	-	-0.246
	1.144	0.24	0.684	-	-0.142	-	-0.007	-0.204
	1.267	0.22	1.211	-	-0.141	-	-0.01	-
1999	0.000	0.18	1.061	-	-0.102	-	-	-
	0.023	0.19	0.659	-	-0.101	-	-	-0.169
	0.954	0.19	1.157	-	-0.1	-	-0.007	-
	1.513	0.21	0.783	-	-0.1	-	-0.005	-0.145
	1.803	0.18	1.024	0.013	-0.103	-	-	-
	1.901	0.19	0.635	0.011	-0.102	-	-	-0.166

Models are ranked by AICc. Shown are all models whose AICc value falls within 2.0 (Δ AICc<1) of the best model (bold). R^2 refers to conditional R^2 . Year was included in the model for all drought years, but its effect was not included in any top models, and coefficients were small (1966: 0, 1977: -0.019, 1999: -0.005; same values in all top models).

Table S7. Summary of top models for each drought instance, where Rt_{ARIMA} is used as the response variable.

drought	$\Delta { m AICc}$	R^2	Intercept	ln[H]	ln[TWI]	ln[H] * ln[TWI]	PLA	π_{tlp}	(1 sp)[novariables]
all	0.000	0.09	1.125	-0.307	-0.506	0.140	-0.012		
	0.425	0.10	0.879	-0.310	-0.508	0.140	-0.011	-0.096	
	1.208	0.09	0.424	-0.060	-0.100		-0.012		
	1.695	0.10	0.178	-0.061	-0.100		-0.011	-0.095	
1966	0.000	0.23	1.660	-0.154			-0.024		
1300	1.393	0.23	1.735	-0.154	-0.047		-0.024		
	1.457	0.23	1.859	-0.152	-0.041		-0.024	0.078	
	1.407	0.20	1.000	-0.102			-0.020	0.010	
1977	0.000	0.16	1.130		-0.180				
	0.424	0.16	2.453	-0.461	-0.896	0.250			
	0.688	0.17	0.720		-0.179			-0.173	
	0.922	0.17	2.040	-0.466	-0.898	0.251		-0.180	
	0.927	0.17	1.248		-0.177		-0.008		
	1.322	0.17	2.569	-0.461	-0.893	0.250	-0.008		
	1.709	0.15	1.183	-0.020	-0.177				
1999	0.000	0.20	0.563		-0.076			-0.200	
1000	0.064	0.19	0.421		0.010			-0.202	
	0.127	0.18	1.036		-0.077			0.202	
	0.256	0.18	1.000		0.011				0.899
	1.777	0.20	0.529	0.016	-0.078			-0.195	0.000
	1.797	0.20	1.101	0.0-0	-0.076		-0.004	000	
	1.815	0.18	0.986	0.018	-0.079		0.001		
	1.838	0.20	0.972	0.0-0	0.0.0		-0.005		
	1.933	0.19	0.391	0.012				-0.199	
	1.979	0.21	0.612		-0.075		-0.002	-0.190	
	1.999	0.21	0.482				-0.002	-0.190	

Models are ranked by AICc. Shown are all models whose AICc value falls within 2.0 (Δ AICc<1) of the best model (bold). R^2 refers to conditional R^2 . Year was included in the model for all drought years, but its effect was not included in any top models, and coefficients were small (1966: 0, 1977: -0.03, 1999: 0.008; same values in all top models).

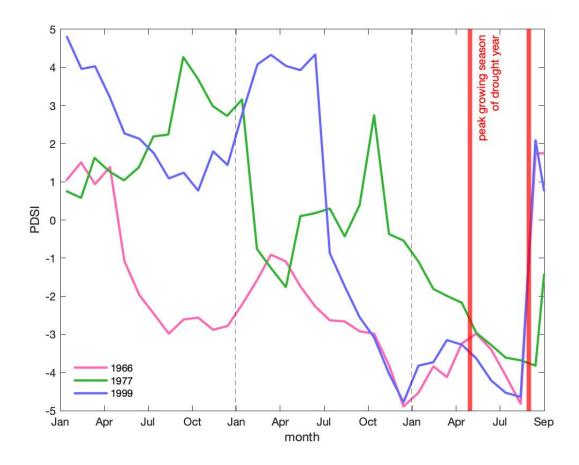


Figure S1. Time series of Palmer Drought Severity Index (PDSI) for the 2.5 years prior to each focal drought



Figure S2. Map of ForestGEO plot showing topographic wetness index and location of cored trees. Scale units are in meters

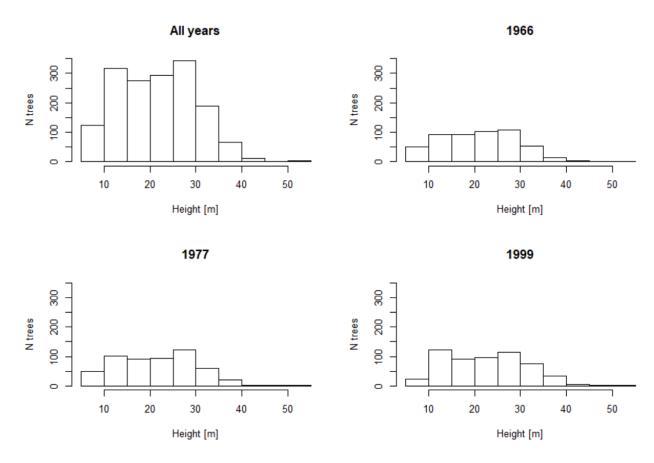


Figure S3. Distribution of reconstructed tree heights across drought years.

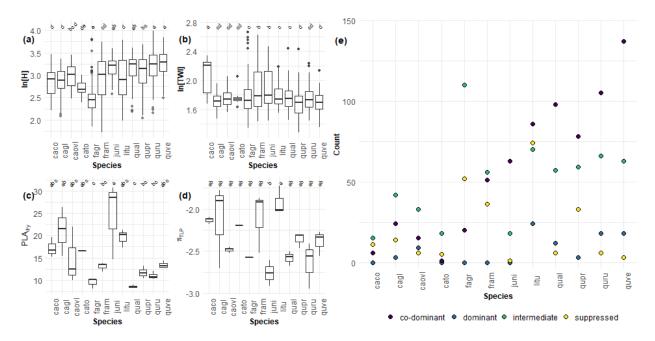


Figure S4. Distribution of independent variables by species. Species that are assigned the same letter are not significantly different from each other with regard to the tested variable.

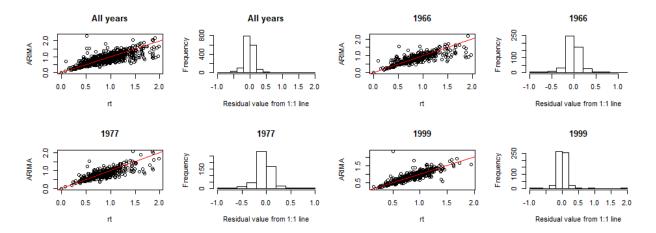


Figure S5. Comparison of Rt and Rt_{ARIMA} results, with residuals, for each drought scenario

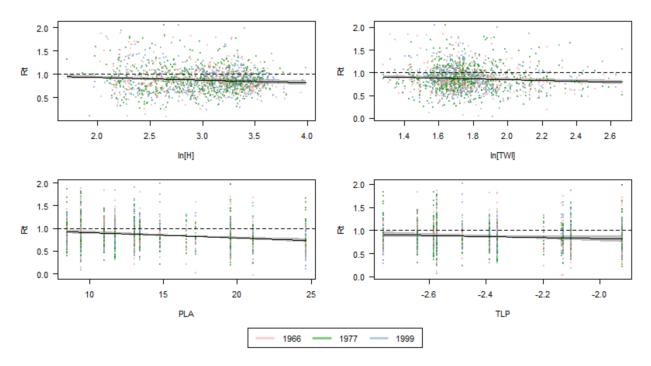


Figure S6. Visualization of the best model ($\Delta AICc=0$) with data for all droughts combined. Model coefficients are given in Table S6.

Further Package Citations

While there were several R-packages we used for a specific purpose in our methods, numerous packages were immensely helpful for this research behind the scenes. As in all of science, this study is a representation of the work done by both the authors of this paper as well as countless others. While acknowledging everyone is impossible, we want to at least give thanks to those who made this work possible.

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